Trail Formation using Large Swarms of Minimal Robots

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Due to the recent advances in robotics, large numbers of robots can be created that exhibit 'swarm-like' behaviour. These robots, typically small and low-cost with restricted sensing, often exhibit Brownian motion similar to micro-particles. The development of algorithms that create collective behaviour that is robust to external pressures has applications in outdoor exploration, search and rescue operations, and nanomedicine. Here, we outline how a swarm of minimal robots, exhibiting only Brownian motion and with limited sensing capabilities, can form trails using mechanisms inspired by diffusion-limited aggregation (DLA). We demonstrate how the trail is robust to obstacles and efficient at finding the closest target. We validate this algorithm both in simulation as well as in reality, using a swarm of up to 100 robots, and highlight the optimum requirements for trail formation.

Keywords: swarm robotics, minimal robotics, chain formation, path formation, reaction-diffusion systems, diffusion-limited aggregation

1. Introduction

Large-scale (10^2 and higher) swarms of simple robots are becoming a reality with applications ranging from environmental monitoring to nanomedicine [2, 8]. Robots that work in such large numbers are typically required to be cheap and, hence, minimal in terms of sensing and actuation [17]. As a result, new swarm algorithms are needed that are robust to noise and limited robot capabilities [5]. Here, we propose a novel strategy for trail formation that takes inspiration from a diffusive growth model, namely diffusion-limited aggregation (DLA) [21]. DLA has successfully been used before in simulation to create trees formed by robot swarms [13, 23] as well as to model biological phenomenon [22]. Our work modifies DLA to only create one trail to a single area of interest rather than adopting a tree-like structure between multiple points. Hence, it is more closely related to directed DLA, such as that observed by microbial communities [18]. We evaluate our control mechanism in simulation and verify the qualitative properties using a swarm of up to 100 real robots. We show that trails are formed to the nearest area of interest when two are present, and that they are able to bypass obstacles. Rather than improve the performance of trail formation in comparison to other algorithms, our focus is on designing an algorithm that works with minimal robots.

Previous work on bio-inspired robotic trail formation has often taken inspiration from the ability of ants to create trails when foraging for food [3]. Work by Vaughan et al. studied the foraging behavior under the assumption that robots have global positioning and global communication [19]. Systems that only use local information may rely on external beacons which can either be existing objects within the environment, as is the case with the redeployed sensors [15], or can be deployed dynamically by the robots themselves [1]. Beacons can also be used for indirect (so-called stigmergic) communication, mimicking the pheromones used by ants such as by storing 'pheromone' information within the beacons [12].

Alternatively, the robots may act as the beacons rather than relying on other types of agents or sensors for communication. This can be achieved with robots dynamically switching between beacon and exploration behaviors [10], or through the use of shortrange communication to transmit a virtual pheromone gradient [16]. Implementations of the former include the formation of robotic chains for target localization [14, 20] or to order tasks [4], as well as the creation of communication networks using flying robots [9].

Many of these systems have required robots to move in a directed fashion, for example to follow pheromone trails. However, deploying large numbers of robots that can perform foraging tasks in large-scale environment requires further constraints on the agent capabilities for it to be cost-effective. For example, it may be difficult to equip every robot with a GPS or calibrate their motion precisely. Given that searching a large area, such as a forest, may require tens of thousands of small safe-by-design robots, algorithms simplicity is of paramount importance. Here, swarm robots can gain inspiration from micro-systems in nature which typically rely on diffusion and reaction of millions of molecules or cells to interact over proportionally large areas [8].

In this paper, we demonstrate the formation of trails using such minimal robots. Applications for trails formed by these robots include guiding a crowd to an exit in an emergency situation, or leading a search team to an area of interest [7]. We describe the algorithm, and simulations used to validate, for trail formation in section 2 and present our results in section 3. We demonstrate that this algorithm can effectively form trails both using simulations and using minimal robotic swarms. We then discuss these trails in section 4 and offer a closer look at the underlying parameters, before making our concluding remarks in section 5.

2. Methods

In this section, we describe and formalise the trail formation algorithm used by agents in both simulations and demonstrated on micro-robots. We begin by discussing diffusion limited aggregation and use this to motivate the algorithm before describing the simulations.

2.1 Trail Formation Algorithm

Diffusion Limited Aggregation (DLA) is the process by which agents aggregate following diffusion, leading to tree-like structures [11]. A seed agent is located at the center of a circular environment (or a sphere in a three-dimensional case) and other agents are released from the perimeter of the circle. These agents start an unbiased random walk until they either leave the environment or encounter the seed, in which case they stick to it. After a few iterations, clusters of agents like the ones shown in Figure 1 will begin to form. This process forms the basis for our trail formation algorithm.

We aim to design aggregation patterns inspired by DLA processes in order to create a distributed control strategy, capable of creating trails without relying on directional control. We will demonstrate that stochastic processes such as DLA can be useful for designing minimal robots to locate areas of interest, even when the individual robots have extremely limited capabilities or are faced by physical obstacles.

We first define both a source and an area of interest within a circular open environment. The source is placed at the center of the circular environment and the area of interest at a fixed distance. The area of interest emits a signal within a limited range,$r_{interest}$. New robotic agents are released at a constant rate, r_{rate}. Agents exhibit Brownian motion with constant speed v through the environment. If an agent finds itself within the transmission range of a signal, $r_{interest}$, it will stop moving (henceforth referred to as binding) and begin emitting a signal to robots within a prescribed communication range, r_{comm}, for time t. Likewise, mobile agents that enter the signal range of a bound agent also immobilise and emit a signal for a time t . The pseudo-code for this algorithm is given below.

2.2 Simulation

We model idealised robots as particles using GAMA[1], a platform for building spatially explicit multi-agent simulations, designed by Grignard et al. [6]. The advantage of this approach is that we can easily test large-scale systems on the order of 103 agents.

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1 https://github.com/gama-platform

Dimensionless parameters are used in these simulation with the goal of improving our overall understanding of the proposed algorithm, rather than optimising the algorithm for a specific use case. Parameters used for the simulated scenarios, unless stated otherwise, are r_{rate}=1, $r_{interest}$=20, v=65, r_{comm}=20, t=50. Simulations are run until a trail is formed, or up to maximum duration of 1000 (simulation) timesteps. For repeatability, the software and parameters used are provided at http://hauertlab.com/software.

3. Results

In Figure 3, we show how the diffusion time (defined as the number of timesteps the agents are in a diffusion state and, hence, unbound) of the agents becomes smaller as agents are added at the source; agents released later during the simulation will spend less time diffusing on average. This is due to the fact that with the continuous release of new agents from the source, the number of agents that bind closer to the source is higher than the number of agents binding further away. The agents emitting a signal when far from the source will eventually stop emitting, further increasing the bias for binding close to the source. This leads to the clustering of agents and the formation of the trail visible in Figure 2. When the trail eventually reaches the source, the high-number of agents emitting a signal will cause any new agent released to bind immediately, effectively blocking the diffusion of newly generated agents. This blocking of the source, together with the fact that agents only emit signal for a short period of time, avoids the further development of new branches.

In Figure 4, we show how the binding distance from the source (averaged over five runs). Again, we observe that the agents bind closer to the source as both time increases and the total number of agents in the system increases. Eventually these agents block the source, leading to the formation of a trail. At the point of trail formation, the distance remains flat until the end of the simulation.

3.1 Overcoming Obstacles

Having demonstrated that this algorithm results in trail formation, we next consider whether the trails are able to overcome environmental changes to test for robustness of behaviour and emergence within the system. We consider the scenario where there are two area of interests that are different distances from the source, such that one is closer. We are interested in whether the trail is able to identify the closer of the two area of interests through only DLA like processes. All parameter values are as described previously.

As shown in Figure 5, the trail grows both areas of interest following the mechanism described in Figure 2.1. However, as one of the trails is closer to the source, the probability of one agent binding to it increases. This results in more agents that are likely to bind near to this area of interest. In fact, even when agents begin to aggregate around both areas of interest, the trail from the area of interest which is placed closer to the source grows faster and reaches the source first. Once the trail reaches the source, all subsequent trails are prevented from forming and the other area of interest is blocked off. This is shown in Figure 5.

Even though no agents have any information about the distance between either area of interest, the closer one will be chosen once the trail has formed. This highlights an emergent property within the system, where the swarm is able to calculate the nearest area of interest without any individual agent explicitly obtaining additional information about the system. This highlights the potential application of this mechanism as a searching algorithm. We have also considered the case where two area of interests are situated at an equal distance from the source. In this case, there is the possibility of creating two trails and small differences in the number of agents initially clustering around one of the areas of interest can lead to one of the trails not being reached.

In many real-world applications, there are significant obstacles present in the environment which prevent pure diffusion. To see how our algorithm is capable of overcoming these obstacles, we introduce a rectangle block between the source and the area of interest. In Figure 6, we show an example trail which has formed around the obstacle to successfully connect the area of interest and source. Here, it is possible to observe how the trail grows around the obstacle from the area of interest back to the source. However, this required that we increased the speed of the agents to $v = 100$, indicating a speed dependence for effectively building trails when obstacles are present in the environment.

3.2 Robotic Validation

We validated the results obtained in simulation using a robotic swarm (Figure 7). This validation is important because much of the cited work [1, 10, 13, 14, 20] is based either exclusively on simulations or on experiments with a small number of robots. We used the Kilobot system [17], a low-cost robotic platform designed to scale to many-robot experiments. The Kilobot (shown in Figure 8) is small (≈3cm in diameter) and moves with a maximum speed of 1 cm/s using two vibrating motors that allow it to turn and move forward. It can communicate in all directions with nearby robots within 10cm using infrared light. Once programmed, the robots are fully autonomous and do not rely on any external input to operate. Experiments are performed on a 2m x 3m arena with videos being captured through an overhead camera. Experiments are stopped as soon as a trail has been formed.

To implement the rules described in Algorithm 1 with the robotic swarm, we need to make the robots diffuse in the environment. We programmed each robot to randomly choose a turning direction (left or right) with equal probability and then turn for a random number of seconds before going straight for another random time interval. The robots are not identical and have differences in turning speed and a direction bias when they go straight (it is not possible to calibrate the two vibrating motors for highly precise straight motion). These inaccuracies are present on an individual level and do not cause a global bias on the entire swarm. The release rate of the agents used in simulation has been replicated by manually placing three robots every 2.5 min. Robots stop being released when the trail has formed to the source, which typically takes more than one hour. The precision of this method is also constrained by human error while timing the intervals. The goal of the experiments was not to obtain highly precise experimental conditions, but rather observe if the overall behavior and qualitative properties of the system showed in simulation could be replicated despite all the experimental constraints. Applications in real world systems will likely involve similar or greater constraints.

We performed the experiments with the robots three times for each of the scenarios. In Figure 8 and Figure 10, we can see a qualitative comparison of the results between the robot experiments and the simulations. The robotic experiments showed that the three main properties observed in simulation can be replicated with the robots. The first property shown in Figure 8 is the ability of the system to form trails. We can also observe the emergence of secondary branches among the trail, as in simulation. A video of this behaviour can be found at https://youtu.be/qZXnq8wYCoU. The second property is the capacity to find the closest area of interest without actively sensing any information related to distance. Figure 9 shows the robots forming a trail towards the area of interest, which is situated closer to the source. This result is also consistent with the results obtained in simulation. Finally, the ability to form a trail around an obstacle was tested with the robots, as shown in Figure 10 (bottom). As in simulation, the robots are able to grow trails from the area of interest to the source while bypassing the obstacle. The trail closely follows the contour of the obstacle, representing the ability for emergent information about the environment to develop within the trail.

4. Discussion

We have demonstrated a novel algorithm for trail formation, inspired by DLA and validated both using simulation and swarm robotics. In subsection 3.1, we have shown that the trail is able to overcome several realistic scenarios such as spatial obstacles or multiple area of interests. Furthermore, we were able to recreate this behaviour using a minimal robotic swarm, described in Figure 3.1. However, we find that trails are not guaranteed to form under all circumstances.

In Figure 11, we show the impact of the release rate on trail formation. Here, we increased the release rate to $r_{\text{rate}} = 30$ and the communication radius to $r_{comm} = 26$. These simulations show a less concentrated distribution of agents within the environment and no visible trail. We compute the root mean square error of the distance for all agents from the minimum distance between source and area of interest. For the first set of parameters, we find that, the root-mean-square error is RMS= 169, whereas for the second set of parameters it is RMS= 204. The performance decrease reflects the different density of agents present in both simulations when the first agent binds to the area of interest. In the second simulation, this allows for agents to rapidly bind to neighbors in all directions without forming directional patterns.

This suggests that a key aspect to obtain efficient and highly directional trails is to control the release of agents and therefore the density of agents at the time of the first binding event. In order to better understand this behaviour, we consider how various parameters can influence the system. We are interested in both the conditions that allow for trail formation to occur (opposed to collection of bound particles that fails to reach the area of interest) and the quality of resulting trail. In order to quantify the system, we consider several metrics.

First, we consider whether a trail has formed. We also calculate the RMS error between the perpendicular distance for all particles and the shortest distance between source and area of interest. Finally, in order to better quantify the success of the trail, we use two features from graph theory: the shortest path between two points and the average network clustering coefficient. To achieve this, we consider the trail as a network of N nodes, where each node represents a bound particle and calculate the shortest distance as the minimum number of hops between start and end point of the trail. The average network clustering coefficient of the trail is the average of all local clustering coefficients which describe how close all neighbours are to being a complete graph. This highlights two potential trails that might be formed, one which is directed such that clustering is small and another 'bushy' trail that covers a larger area and has higher average clustering coefficient. We discuss the formation of both types of trails below.

Given the metrics described above, we consider how the release rate, r_{rate} , communication radius, r_{comm}, and speed of the particles, v, affects the trail. A further question is how the evaporation rate of the emitted signal (by individual agents) affects the trail. Such questions will form the basis for future research. We repeat each simulation using the same initial conditions as described in subsection 2.2 for $r_{rate} = \{1, 6, 11, 16\}$, $r_{comm} = \{10, 20, 30, 40, 50\}$, and $v = \{25, 45, 65, 85\}$ and run each combination of parameters four times to account for the stochasticity within the system. We set an upper bound of 2000 agents to reduce computation time and extend total simulation time to 2000 cycles. In Figure 13, we show the final distributions of bound particles for several example simulations.

In Figure 13, we find several qualitative types of trails forming. First, we note that trail formation fails to occur when the communication radius is low (rcomm $\leq$ 20), shown in (a), (d), (g) and (j). This is because binding occurs predominantly near to the area of interest such that many particles are needed to form a trail to effectively bridge the distance between source and the area of interest. However, an increased release rate or faster agents does not necessarily overcome the restrictions from the communication radius. This is demonstrated by (a) which has the furthest of all trails. Instead, it is likely that trail formation occurs slower such that the simulation would need to be run for more cycles. As the communicate range increases, from left to right, trails are more likely to occur.

Given a trail, we next quantify the type of the trail formed using the network metrics described above. For all release rates, the path length is lowest for fast particles with large communication range, demonstrated by ??. However, as release rate increases, the speed of the particle has less effect (less than 2 difference in minimum hop count across speeds for $r_{rate} > 6$ and $r_{comm} > 20$). This can be understood as higher release rate causing the environment to become filled with agents, as shown in in Figure 13(e), compared against (a), and (f), compared against (c). Hence, when a trail is formed, the shortest path is available from the large number of nodes within the trail.

The clustering of the trails is unaffected by particle speed or communication radius for high release rates ($r_{rate} > 1$). However, when the release rate is low ($r_{rate} = 1$), there is a distinction between low speeds and high speeds, shown in Figure 13. This highlights that directed trails occur when speed and release rate is low, where the majority of particles have not travelled a large distance from the source before reaching the area of interest. At these low release rates, the slow particles create a strong gradient of particles to emerge from the source to the area of interest. When the first particle binds to the area of interest, the trail then grows in the direction of the gradient.

Alternatively, fast particles with high release rates rapidly distribute over the entire environment, creating bushy trails. Shown in Figure 13(e) and (f), where the bound particles cover a larger area than when release rate is low. These trails are more robust to agents becoming unbound but require more agents to bind. Furthermore, the mean square error of the distance for each agent is higher than the directed trail, implying that many agents are redundant. The average mean square error for the trails increases for both communication radius and area, as shown in Figure 12(b). These parameters highlight two qualitatively different types of trails that can be achieved using this algorithm. It is possible to build directed trails with minimal number of agents when the agents are slow and have short communication radius. This results in more efficient use of agents (others can be deployed back once a trail has been formed) but is more prone to breaking due to the fewer links between agents (lower average clustering coefficient). Alternatively, fast agents and slow agents with large communication radius create bushy trails. The bushy trail may be more appropriate for covering a larger field of search while directed trail formation may be more applicable to scenarios where a single area of interest is sought.

5. Conclusions

In this paper, we have presented a swarm strategy for simple robots that is inspired on diffusion limited aggregation to form trails. As we have shown, this strategy is able to find the closest area of interest in the environment where two competing areas are present, and is able to adapt to the environment, such as by overcoming obstacles. Such emergent behaviour is typical of swarm like systems and highlight the complexity of behaviour that can be achieved when utilising large numbers of minimal agents and highlights the strength in using bio-inspired mechanisms for informing algorithm design.

Declaration of Interests

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Figures

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if not bound then
    if sense signal then
        set state to bound;
    else
        perform random walk;
    end
else
    stop motion;
    if time smaller than maximum signal time then
        emit signal;
    end
end
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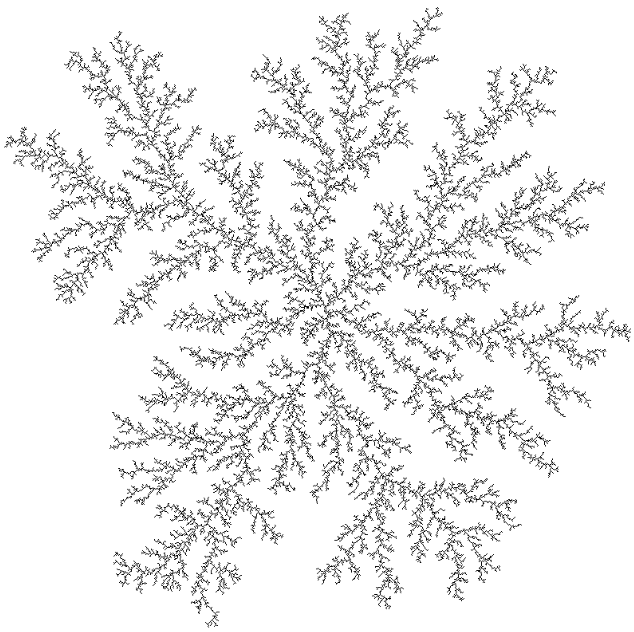

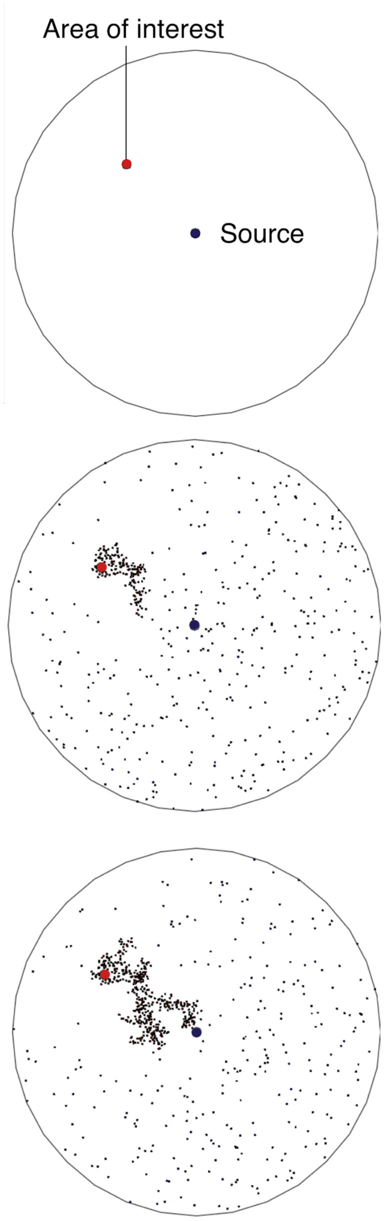
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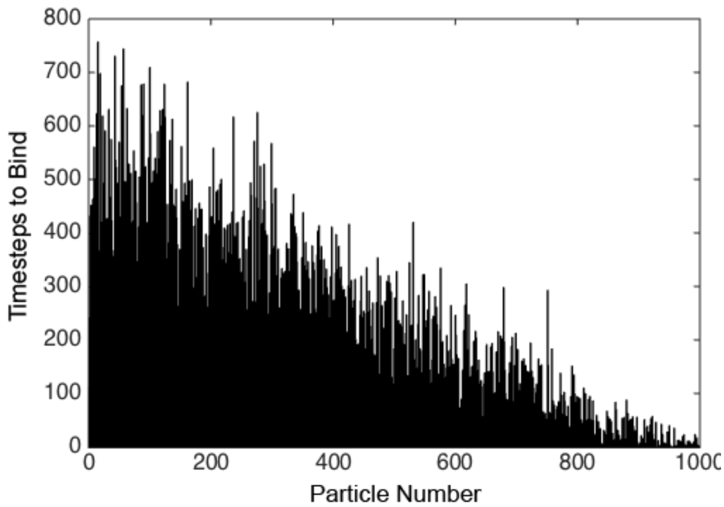
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800
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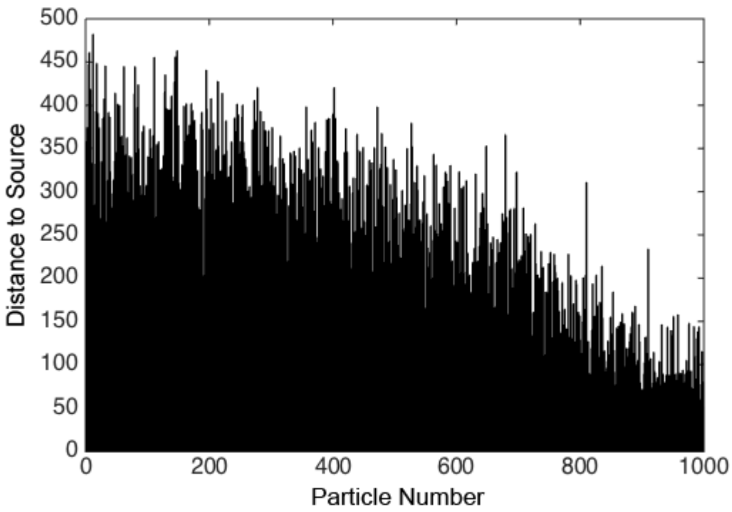

Distance to Source
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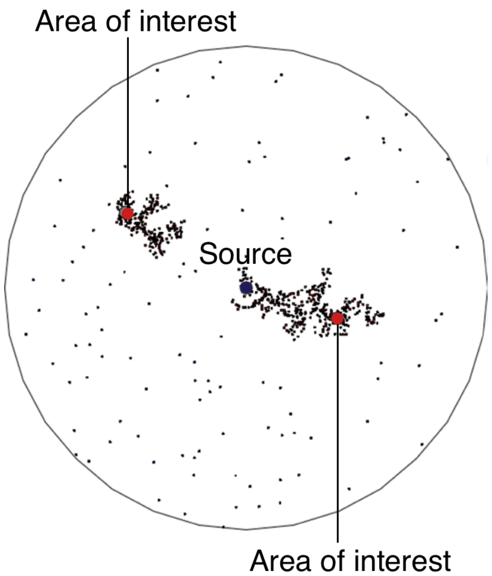

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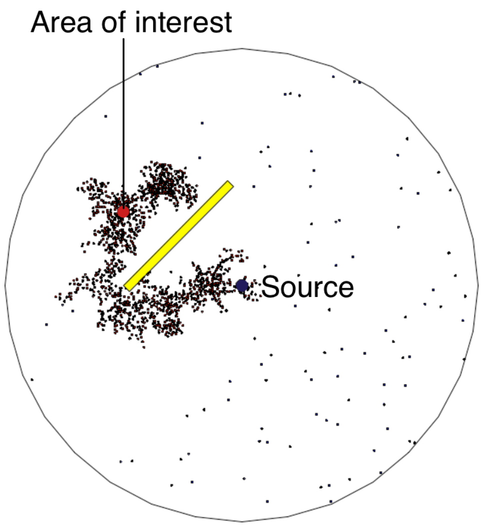

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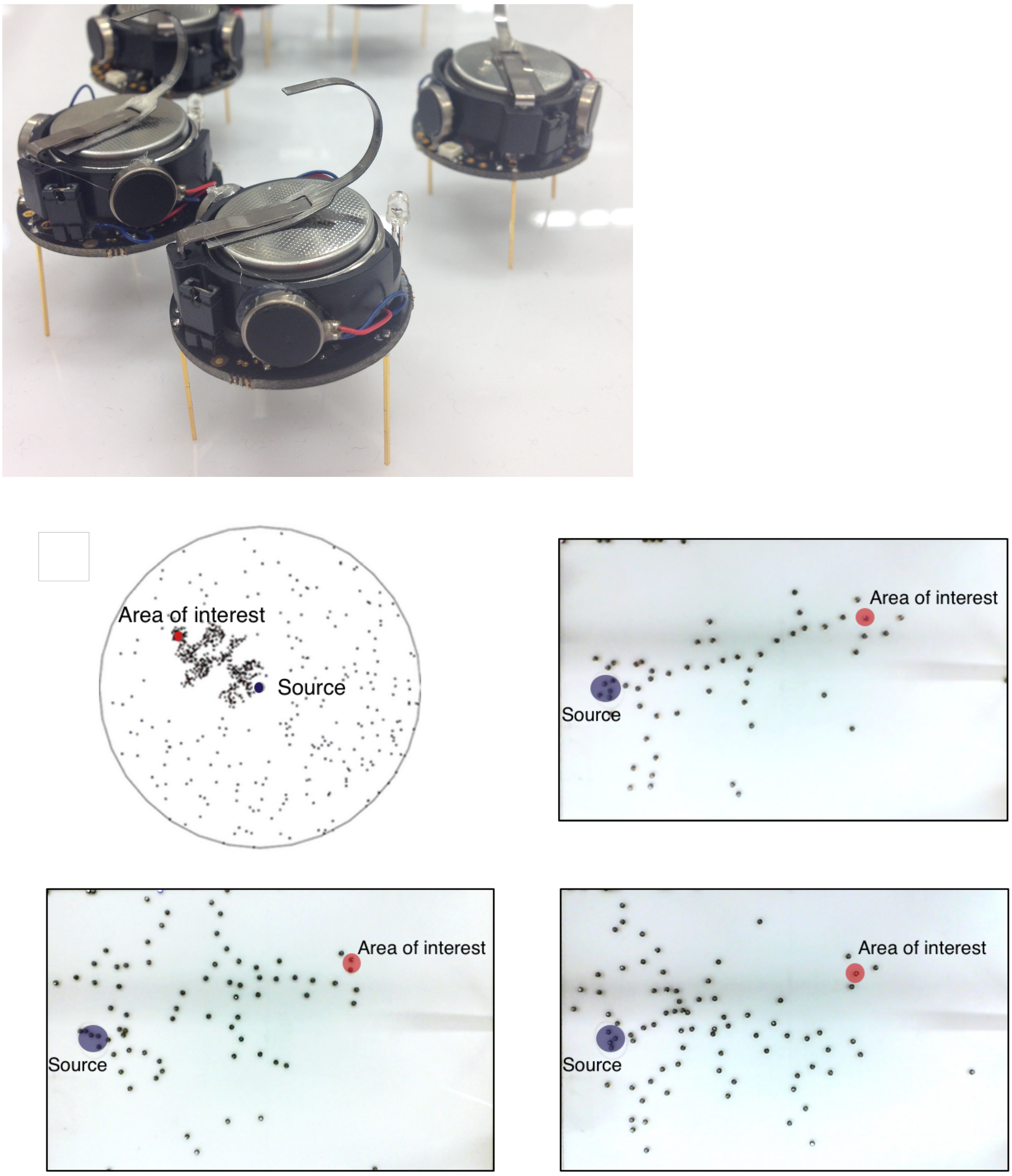
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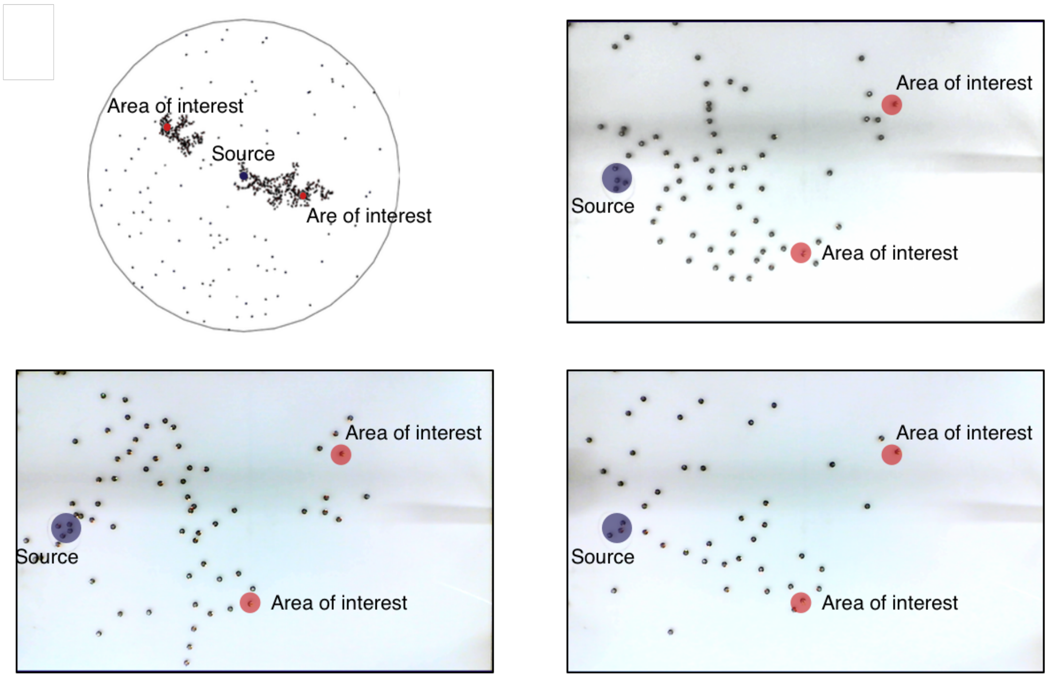
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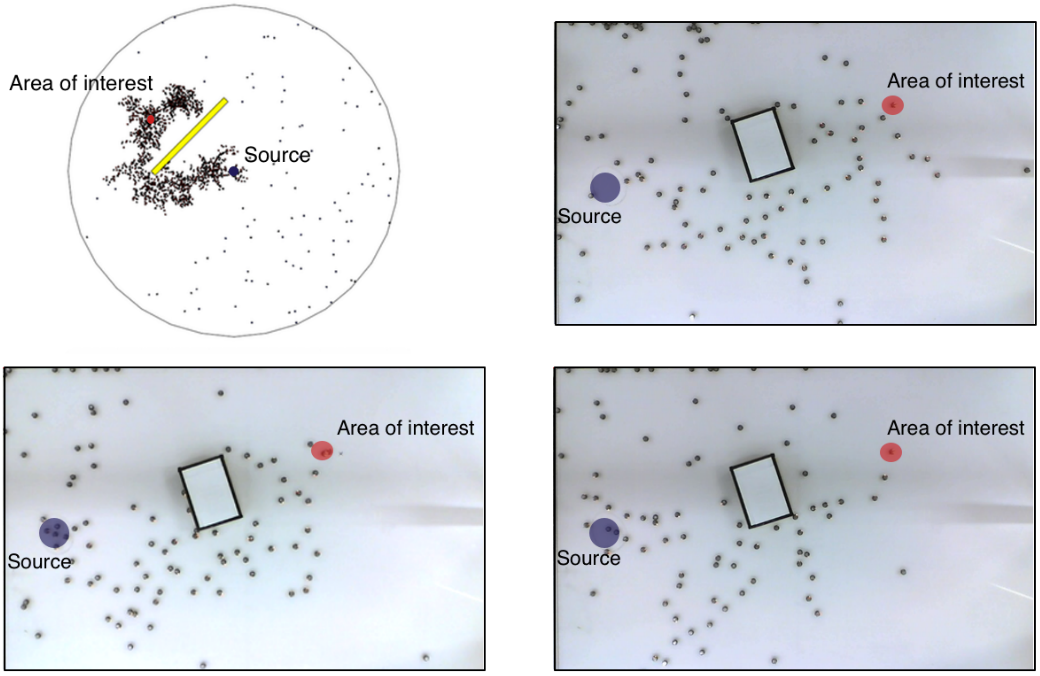
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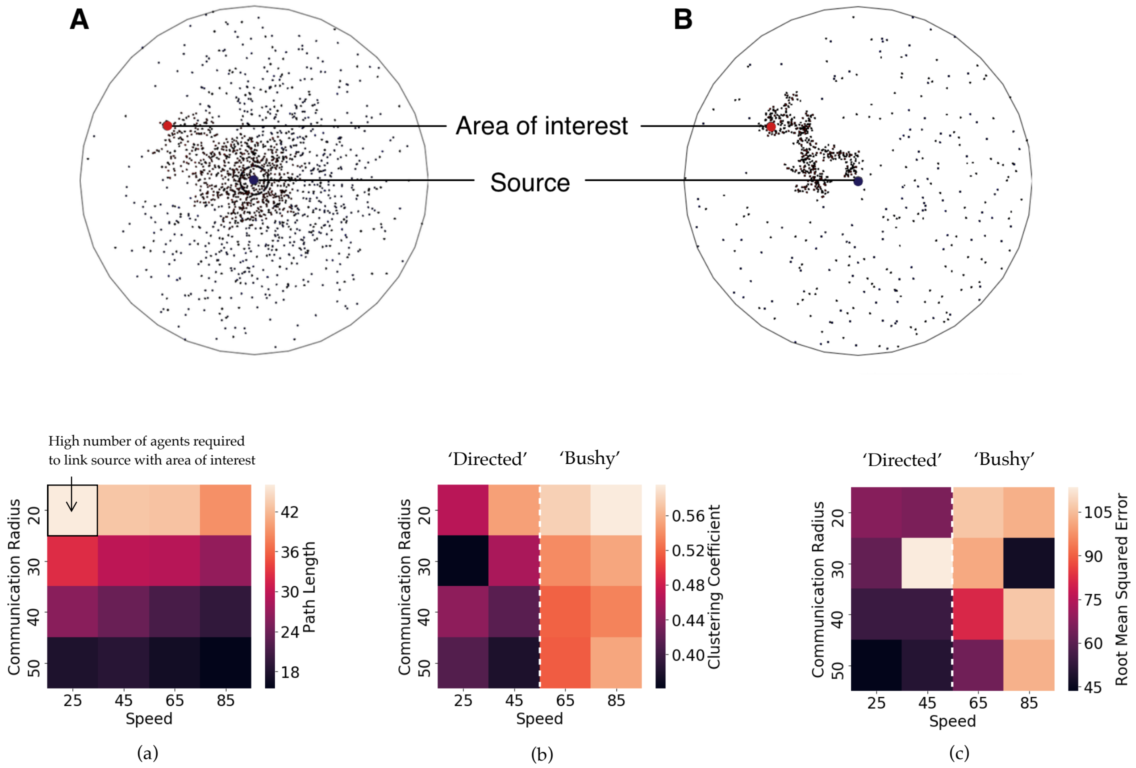
A
B
Area of interest
Source
High number of agents required
to link source with area of interest
Communication Radius
20
30
40
50
25
45
65
85
Speed
Path Length
42
36
30
24
18
(a)
'Directed'
'Bushy'
Clustering Coefficient
0.56
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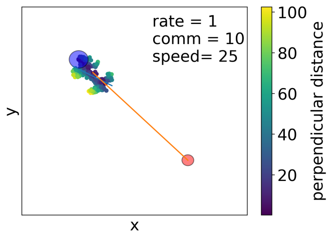
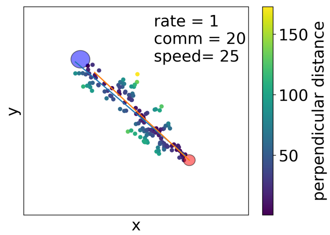
0.48
0.44
0.40
(b)
Root Mean Squared Error
105
90
75
60
45
(c)



(a)



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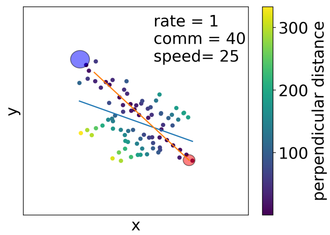
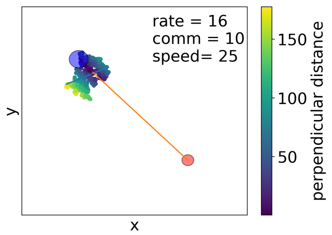


(c)



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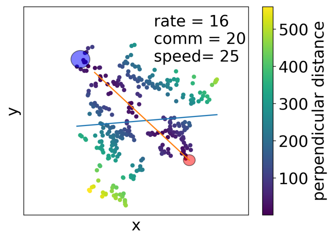

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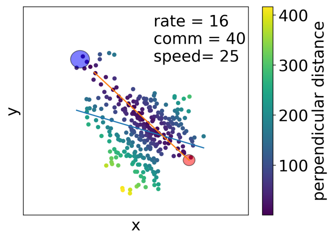

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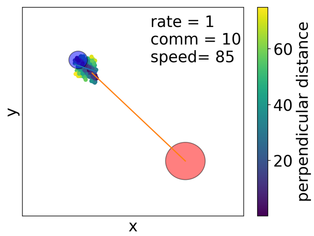

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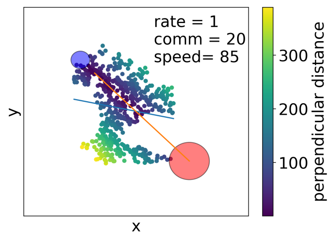

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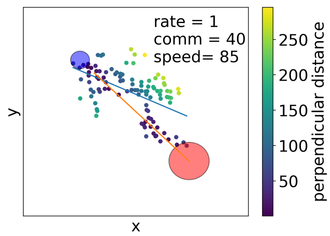
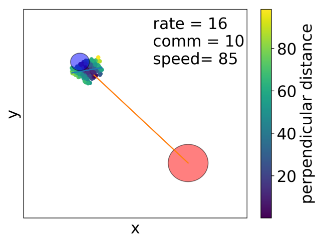


(i)



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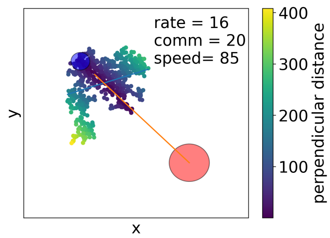

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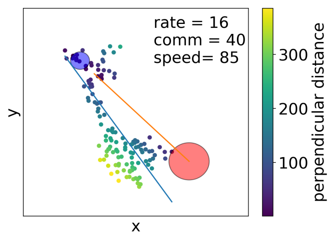

(l)

Figure Captions

Algorithm 1: Pseudocode for the trail formation algorithm.

Figure 1. Structures formed by DLA with a seed agent at the center of the environment. Image by Paul Bourke[2].

Figure 2: Snapshots of a simulation on a circular environment with a source in the middle, and an area of interest located within the environment. The circle on the top shows the environment before the simulation starts. The image in the middle corresponds to a snapshot taken during runtime, and the bottom image represents a snapshot taken at the end of the simulation. A trail can be seen growing from the area of interest to the source.

Figure 3: Average number of timesteps (over 5 runs for the same scenario) taken by agents to bind, as a function of their release order from the source. Agents released later bind quicker on average.

Figure 4: Average distance from the source (over 5 runs for the same scenario) at which agents bind, as a function of their release order from the source. Agents released later bind nearer to the source on average.

Figure 5: Final snapshot of a simulation with two areas of interest, with the area of interest on the right placed closer to the source. The trail is formed to the nearest area of interest.

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[2] http://paulbourke.net/fractals/dla/

Figure 6: Final snapshot of a simulation with an obstacle between the source and the area of interest. The trail is successfully formed to the source while bypassing the obstacle.

Figure 7: Up to 100 Kilobot robots were used for swarm experiments.

Figure 8: Trail formation at the end of the simulation (upper left), and at the end of the robot experiment for three trials. In all cases, trails are formed to the area of interest.

Figure 9: Trail formation at the end of the simulation (upper left), and at the end of the robot experiment for three trials. Two areas of interest are present in the environment, with one of them placed closer to the source. In all cases, trails are formed to the nearest area of interest.

Figure 10: Trail formation at the end of the simulation (upper left), and at the end of the experiment for three trials, when an obstacle is placed along a direct line between the source and the area of interest. In all cases we can observe the adaptation of the trail to circumvent the obstacle.

Figure 11: Impact of the release rate and communication range on trail formation. Scenarios with higher release rates and larger communication ranges (A) form worse defined trails than scenarios with lower release rates and communication ranges (B).

Figure 12: Comparison of the influence of the communication radius and speed of an agent for forming trails, where release rate is $r_{rate} = 1$ and we have not included $r_{comm} = 10$ which does not result in a trail. We find that (a) the shortest path length is lowest for slow agents with short communication radius, (b) that increasing the speed of the agent increases the average clustering coefficient as well as the RMS error in shortest distance from source to trail. This highlights that the most directed trail is those that have are slow with short concentration radius.

Figure 13: Example distribution of bound particles under different system parameters, where rrate = {1, 16}, v = {25, 85}, and rcomm = 10, 20, 40}. The first two rows show low speed and second two rows show high speed, whereas columns show increase in communication radius. The release rate is low for the first and third row and high for the second and fourth. In each simulation, the source is marked by a red circle and the area of interest by a blue circle, with the shortest distance between both marked a a red line. The source size scales with agent speed so as to detect first trail formed. The line of best fit for all agents is marked as a blue line and each agent is marked by their perpendicular distance from the shortest distance between area of interest and source. Note that for low communication rate, no trail is formed. However, for higher communication rate, we see multiple trails. When speed and release rate is low, trails are most directed, while higher speed and release rate results in more distributed trails.